The importance of regionalized LCIA in agricultural LCA – new software implementation and case study

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ABSTRACT

The necessity of performing regionalized LCA in agriculture derives mainly from the wide variety of existing farming systems and the influence of site-specific characteristics (e.g. climate, soil type, water availability) on the environmental impacts. Challenges on linking regionalized inventories and LCIA methods which use different spatial scales may be overcome by integrating GIS in the calculations. A new approach for GIS-based LCIA has been implemented in the open source software openLCA with the support of the USDA, where the calculation of regionalized characterization factors is parameterized using site-dependent and substance-dependent properties. The regional parameters are stored as attributes of each geolocalized element in shape files. The approach has been implemented in a case study on corn production in five US states. LCIA results from the Ecological Scarcity 2013 and enhanced Ecoindicator99 (EI99+) methods varied significantly between locations and, even more, depending on the spatial support used for the regional parameters.

Keywords: regionalized LCIA, openLCA, GIS, corn case study

1. Introduction

Environmental life cycle assessment (LCA) of agricultural systems commonly focuses on the impact categories land use, eutrophication, toxicity, acidification, climate change or depletion of abiotic resources (Bentrup *et al.* 2004; Payraudeau and Van der Werf 2005; Harris and Narayanaswamy 2009). The necessity of performing a regionalized life cycle impact assessment (LCIA) derives from the fact that the characterization factors in the majority of these impact categories are dependent on site-specific characteristics (e.g. population, soil types, climate factors, etc.). Appropriate spatial scales have to be selected for defining each of these different variables in order to minimize their spatial uncertainty (Manneh *et al.* 2010). However, this usually leads to a heterogeneity of spatial units within impact categories, which makes the calculation of the characterization factors at the resolution required by the inventory data more difficult (Gotway and Young 2002; Perveen and James 2009). Geographic differentiation of processes in an agricultural life cycle may also vary from global to farm level, usually prevailing site-specific modelling in data sets of the foreground system. Consequently, the ability to deal with multiscale systems without compromising the correctness of the results is fundamental in a regionalized impact assessment (Halog and Bortsie-Aryee 2013).

Geographic information systems (GIS) have been used by several authors to integrate spatial differentiation in LCA, not only for the calculation of regionalized characterization factors but also for creating site-specific inventories and matching each of these (Bengtsson *et al.* 1998; Geyer *et al.* 2010, Nuñez *et al.* 2010; Mutel *et al.* 2012; Liu *et al.* 2014). Moreover, Gerber *et al.* (2013) stated in a report of the food and agriculture organization of the United Nations (FAO) the convenience of using GIS for incorporating spatial heterogeneity into the modelling process and Halog and Bortsie-Aryee (2013) also recommended GIS as a powerful tool for supporting regionalized LCA.

Considering the importance of performing regionalized LCAs in activities such as agriculture and the feasibility of linking spatially differentiated inventories and impact methods using GIS, the integration of the functionality to conduct fully regionalized LCIA should be a priority for LCA tool developers. This paper aims to present a new implementation approach for GIS-based regionalized LCA developed in the open source software openLCA. The application of this new feature in a case study on corn production in five different states of the United States is also examined.

2. Methods

2.1. Extension of geographic information in process data sets

In contrast to the tendency in impact assessment methodologies where more detailed regions (e.g. watersheds, ecozones, etc.) are used for the definition of the characterization factors, most commonly used LCA databases (e.g. ecoinvent 3, GaBi 2013, ELCD3) continue using country or group of countries locations only. However, spatial differentiation of agricultural systems usually requires higher spatial resolution geographies due to the considerable diversity of farming systems (Pradeleix *et al.* 2012). Therefore, the feature for specifying the geographic information of the process in openLCA needed to be enhanced to allow the LCA practitioner to differentiate between site-specific locations and to integrate GIS information in the data sets.

Data exchange formats most commonly used in LCA tools (i.e. EcoSpold1, ILCD, EcoSpold2) are all based on extended markup language (XML). The geographical information included in them has evolved from the limited location code of EcoSpold 1, to the addition of a latitude and longitude pair in ILCD and finally to the integration of keyhole markup language (KML) geographic descriptions in EcoSpold2 (Mutel 2009). As the geospatial information stored in KML files can be used by GIS, a KML editor for the processes was added in openLCA (Fig. 1). In this editor, the process location can be defined using three geometrical primitives (i.e. point, line and polygon). The resulting geographical information, characterized by the object's geometry and a set of coordinates, is known as the spatial support of the dataset (Plumejeaud *et al.* 2010). This spatial support can be easily imported and exported using a slightly modified ecospold 2 format, where KML data is also linked to the process id.

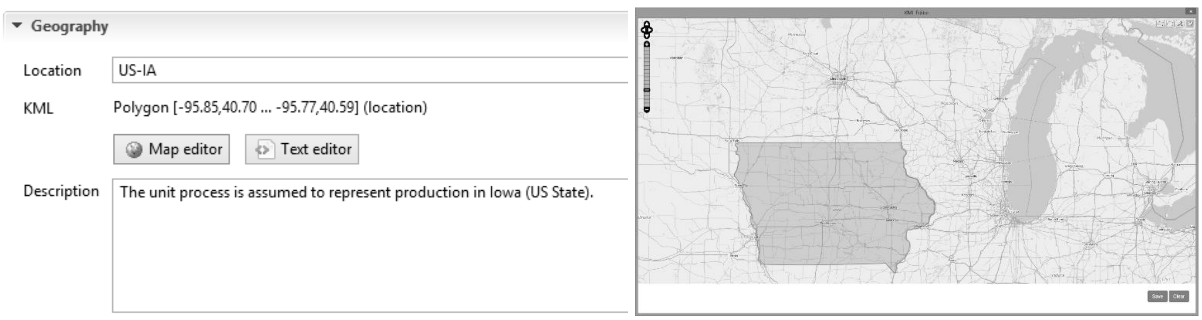

Figure 1. Extended geographic information in a process data set (left) and KML editor (right) (openLCA 1.4)

2.2. Parameterization of regionalized LCIA methods

The availability of impact assessment methods providing characterization factors not only on a site-generic scale but also on a country and sub-country level or even for very high spatial resolution geographies has increased considerably in recent years (e.g. EDIP 2003, EcoIndicator 99+, ImpactWorld+, etc.). The increase in the amount of data resulting from this spatial differentiation of the factors has been overcome by using GIS files as databases of the site-specific characterization factors. However, concerns about integrating all this GIS data in the LCA software without compromising the computing power of the tool fostered the development of a new concept for dealing with regionalized LCIA in openLCA. In this new approach, the mathematical functions used in the LCIA models are parameterized in order to differentiate between site-generic (i.e. dependent on substance properties) and site-specific (e.g. population density) variables. The resulted functions per substance and impact category are defined in the openLCA LCIA method editor (Fig. 2), whereas the data for the regional characteristics are stored in shape files (i.e. GIS vector data) as attributes of each geolocalized element. The data from the different attributes extracted during the import of the shape files can be bound to the parameters used in the characterization factors functions and a default value to be used with site-generic inventory data can also be defined (Fig. 3). Moreover, uncertainty of each characterization factor and parameter can be included. As the shape files are stored in the LCA database, they can be easily exported with the database.

Impact factors

Impact category: Land use_biome

Flow	Category	Flow property	Unit	Factor	Uncertainty
Occupation, arable	resource/land	Area*time	m2*a	((0.60*ratio_biom)/SA_CF)*weighting*c/normalization	none
Occupation, construction site	resource/land	Area*time	m2*a	((0.44*ratio_biom)/SA_CF)*weighting*c/normalization	none
Occupation, forest	resource/land	Area*time	m2*a	((0.04*ratio_biom)/SA_CF)*weighting*c/normalization	none

Figure 2. Impact factors tab in the new LCIA method editor (openLCA 1.4)

Parameters

Global parameters

Input parameters

Name	Value	Uncertainty	Description
ratio_biom	1.0	uniform: min=0.21 max=1.97	from shapefile: ecoregions_with_biome_ratio
SA_CF	0.44	none	Settlement Area BDP biome 5
normalization	2.437E9	none	m2a SA-eq.
critical_flow	3535.0	none	km2
current_flow	3027.0	none	km2
c	1.0E12	none	a-1

Dependent parameters

Name	Formula	Value	Description
weighting	(current_flow/critical_flow)^2	0.7332397584070389	-

Figure 3. Parameters tab in the new LCIA method editor (openLCA 1.4)

2.3. Regionalized LCIA calculation framework

The matrix-based calculation in openLCA needed to be extended to include the geographic variable in the inventory, impact assessment and results matrices. Moreover, in order to handle geospatial data, the open source Java code library GeoTools (2013) was integrated in the software.

The first step in the regionalized LCIA calculation in openLCA is to obtain the inventory matrix *G* which contains all the emissions and resources consumed per process and, consequently, per location as defined in each data set. Then, the regionalized LCIA matrix *C* containing the characterization factors per elementary flow and location in the inventory and per impact category in the method is calculated. To this end, the area of each spatial unit where the regional parameters are characterized intersected by each geographic feature of the inventory is determined. Then, a weighted average value for each parameter is obtained applying equations 1-3, depending on whether a point, line or polygon is used for defining the process location (Fig 4). Once the parameters values are calculated, the formulas in the method are evaluated resulting in the matrix *C*. Finally, the multiplication of matrices *C* and *G* provides the matrix *R* of regionalized impact assessment results.

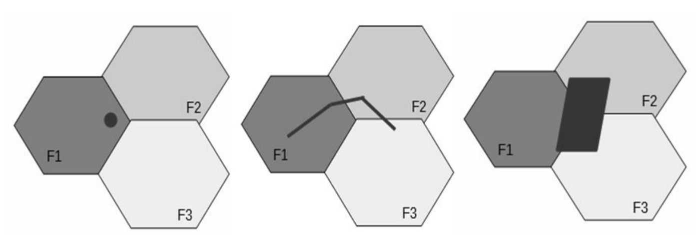

Figure 4. Schematic representation of the calculation of the intersected spatial units from the LCIA method (F_i) by the process geometries point (left), line (center) and polygon (right).

$$p_{Fi} = p \qquad \text{Eq. 1}$$

$$\frac{\sum_{i=1}^{n}\left(p_{Fi} L_{Fi}\right)}{\sum_{i=1}^{n} L_{Fi}} = p \qquad \text{Eq. 2}$$

$$\frac{\sum_{i=1}^{n}\left(p_{Fi} A_{Fi}\right)}{\sum_{i=1}^{n} A_{Fi}} = p \qquad \text{Eq. 3}$$

Where L_{Fi} and A_{Fi} represent the length of the line and the area of the polygon contained in each feature Fi of the shape file (i.e. spatial unit where the regional parameters are characterized), respectively.

2.4. Case study inventory and preliminary impact assessment data

Life cycle models of corn production using cradle-to-farm gate as system boundary were created for the US states of Illinois, Iowa, Nebraska, North Dakota and Minnesota. The LCA Digital Commons (2013) database developed by the United States Department of Agriculture (USDA) and National Agricultural Library (NAL) was used for the activities occurring within the farm. The rest of the life cycle was completed with unit processes from ecoinvent v.2.2 and GaBi 2012 database extension XVII - full US. The KML information of the five states was obtained from the US Census Bureau (2014). The functional unit of the different product systems is the production of 1kg of “corn grain, at harvest in 2005; at farm; 85%-91% moisture”.

The method Ecological Scarcity 2013 (Frischknecht and Büsser Knöpfel 2013) was used for calculating the environmental impacts of the product systems, focusing mainly on the categories land use and freshwater consumption as they include regionalized characterization factors at different spatial resolution scales. The regional eco-factors are obtained applying to the characterization factor (*K*) a weighting factor calculated on the basis of the current (*F*) and critical annual flows (F_k) from a specific region and normalized to the annual flow in Switzerland (F_n^{CH}) (Eq. 4). In the case of freshwater consumption impact category, the weighting factor can be calculated by the ratio of water withdrawal to renewable water supply (i.e. the water scarcity), considering that the critical flow is 20% of the water supply (Eq. 5). The method developers provide a list of the resulting water scarcities on global and country levels, as well as a Google™ earth layer with values per watershed (Treeze Ltd 2014). This GIS data was adjusted to the shape file format required by openLCA (i.e. including the water scarcity values as attributes of the different features) using the free, open source software QuantumGIS. In addition, a shape file containing the country specific eco-factors and water scarcity ratios was created.

$$Eco-factor^{\mathrm{Region\_1}} = K \cdot \frac{1 \cdot UBP}{F_n^{CH}} \cdot \left(\frac{F^{\mathrm{Region\_1}}}{F_k^{\mathrm{Region\_1}}}\right)^2 \cdot c \qquad \text{Eq. 4}$$

$$Eco-factor^{\mathrm{Region\_1}} = K \cdot \frac{1 \cdot UBP}{F_n^{CH}} \cdot \left(\frac{water\_withdrawal^{\mathrm{Region\_1}}}{water\_supply_{renewable}^{\mathrm{Region\_1}} \cdot 20\%}\right)^2 \cdot c \qquad \text{Eq. 5}$$

Where *c* is a constant (i.e. 10^{12}/a) and *UBP* is eco-point, the metric used for expressing the environmental impact assessed.

Regarding land use impact, the Biodiversity Damage Potentials (BDPs) of biome 5 (i.e. temperate coniferous forests) from de Baan *et al.* (2012) are weighted with the ratio of species densities from Kier *et al.* (2005) to biome 5 in order to obtain biome-specific BDPs. “Settlement area” (SA) land use is selected as the reference “substance” for the determination of the characterization factors (K) that derive of the resulting BDPs (Eq. 6). The regional eco-factors are then calculated applying equation 7. This equation is defined per relevant elementary flow in the openLCA LCIA method editor as shown in figures 2-3. For a non-regionalized LCIA, the eco-factors of biome 5 are used (i.e. default ratio of species densities equal to 1). A shape file containing the features of the 14 biomes considered in the method with their correspondent ratio to the biome 5 as attribute was created for openLCA.

$$K^{biome\_i} = \frac{BDP^{biome\_i}}{BDP\_settlement\_area\_biome5} = \frac{BDP^{biome5} \cdot ratio^{biome\_i}\_to\_biome5}{BDP\_settlement\_area\_biome5} \qquad \text{Eq. 6}$$

$$Eco-factor^{\mathrm{Re}gion\_1} = K^{\mathrm{Re}gion\_1} \cdot \frac{1 \cdot UBP}{F_n^{CH}} \cdot \left(\frac{F}{F_k}\right)^2 \cdot c \qquad \text{Eq. 7}$$

Moreover, the impact due to water consumption was also measured using the enhanced EcoIndicator99 (EI99+) method (ETZ Zürich 2014), which provides characterization factors at the watershed and country levels for the midpoint indicator WSI (i.e. water stress index), as explained by Pfister *et al.* (2009).

3. Results

3.1. GIS-based regionalized LCIA implementation in openLCA

The implementation of the new features and calculation framework for regionalized LCIA in openLCA was performed successfully (Fig. 1-3) and without affecting significantly the calculation time required when a single line, point or polygon was used in the geographical specification of the process. However, the ability of dealing with multi-polygons (e.g. countries containing continental and overseas territories) must be refined. Moreover, additional enhancements such as the integration of regionalized LCIA in the project level (i.e. comparison of different product systems) will also be made. The already implemented features were included as experimental in the first release of openLCA 1.4 in June 2014.

3.2. Preliminary case study results

The characterization factors calculated by openLCA varied largely between the states assessed and, even more, within the same location depending on the spatial units used for the regional parameters. Table 1 presents the results for the three impact categories previously described in section 2.4. The WSI from EI99+ was for three states one order of magnitude lower than the US mean value, while Nebraska had a slightly higher value than the country average. The eco-factors for arable land use calculated using biome scale varied also 25.9% between North Dakota, the state with the lowest value, and Minnesota, the one with the highest eco-factor. As the states assessed in this study were located within biomes 4 (i.e. Temperate broadleaf and mixed forests) and 8 (i.e. Temperate grasslands, savannas and shrub lands), it is expected that characterization factors for other states with most sensitive ecoregions (e.g. California) will present even higher differences respect to the generic value (i.e. biome 5).

Table 1. Characterization factors for the EI99+ midpoint category WSI and the Ecological Scarcity 2013 categories land use (i.e. arable land) and freshwater consumption calculated with openLCA 1.4 (beta 6) for five states of the USA, using different spatial resolutions (i.e. country, watershed, biome)

	WSI (m3/m3) – EI99+	Eco-factor for land use, arable	Eco-factor for freshwater consumption

			(UBP/m2a SA-eq.)			(UBP/m^3)	
Location	**Country**	**Watershed**	**Generic**	**Biome**	**Global**	**Country**	**Watershed**
Illinois	4.99E-1	2.81E-2	420	360	610	232	109
Iowa	4.99E-1	5.31E-2	420	325	610	232	7376
Minnesota	4.99E-1	2.89E-2	420	397	610	231	4717
Nebraska	4.99E-1	5.94E-1	420	294	610	232	62532
North Dakota	4.99E-1	1.11E-1	420	294	610	231	45828

The impact category freshwater consumption from the method ecological scarcity 2013 deserves a deeper analysis as huge differences exist between the results obtained using the country-level and the watershed spatial resolution. As reported by Frischknecht *et al.* (2009), the country water scarcity values are obtained from the AQUASTAT database of FAO[1], whereas the data for a deeper regionalized assessment is retrieved from the database of the University of New Hampshire[2], whose indicators are used in the World Water Assessment Program of UNESCO. Specifically, the indicator I4 (i.e. mean annual relative water stress index) with values per grid cell was used to generate unweighted aggregated values per watershed (Fig. 5). The resulting averages per water basin led to extreme water scarcities (i.e. >1) in the areas intersected by some states used in the case study. Consequently, the eco-factors calculated by openLCA with data at the watershed level are much higher than those obtained with the country data.

Figure 5. Mean annual relative water stress index per watershed adapted from Treeze Ltd (2014) for its use with the ecological scarcity method 2013

The results for impact categories for which no regionalized characterization factors were available varied also between the product systems analyzed, as different inventory results were obtained due to the state-specific data sets used for the farm activities. Figure 6 presents the LCIA results of the Ecological Scarcity 2013 method. It can be observed that Nebraska is the state with highest environmental impacts for most of the impact categories, except for land use where North Dakota and Minnesota had the higher impacts. This reinforces the idea that the availability of regionalized inventories when performing site-dependent LCAs is as important as having regionalized characterization factors. For instance, if the same inventory had been used for all states, Minnesota and not North Dakota would have been the farming system with highest impacts due to land use.

[1] http://www.fao.org/nr/water/aquastat/main/index.stm

[2] http://wwdrii.sr.unh.edu/download.html

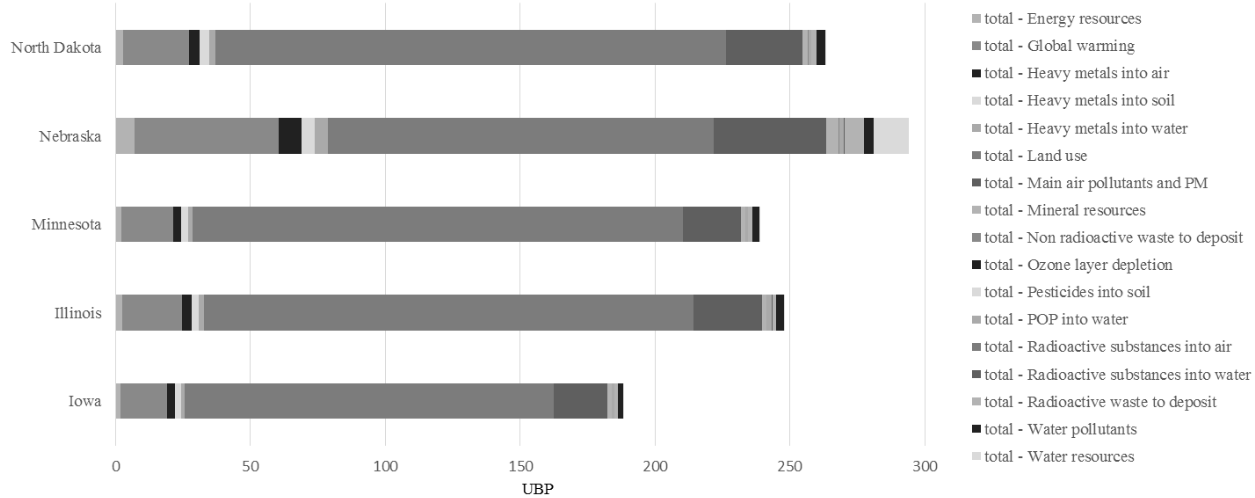

Figure 6. 1kg corn grain production LCIA results in UBP for the Ecological Scarcity 2013 method (regionalized assessment of land use and water resources impact categories). Results calculated for farming systems in Illinois, Iowa, Minnesota, Nebraska and North Dakota.

4. Discussion

The variety in the results obtained from the calculation with different spatial scales showed the convenience of using non-aggregated data for the characterization of the regional parameters in the LCIA methods. However, for some factors, division at the cell level (e.g. per square meter) might lead to missing some important regional conditions relevant to the effect of the emission or resource consumption. For instance, Frischknecht *et al.*, (2009) described that water stress modeling at the cell division level does not consider hydrological conditions; the result of this is that areas suffering from great water stress lack water stress values in the model because no water extraction takes place there, (i.e. large parts of the Sahara). Thus, it is necessary to determine the most suitable spatial resolution to use for each parameter so that all the relevant regional properties are considered and their spatial uncertainty is minimized. The use of weighted aggregations might be useful for avoiding misleading values such as in the case of the WSI of Figure 5. To this end, available data on background emissions or likely geographical distribution of emissions (i.e. emission proxies) could be used to determine the areas where the probability of occurring the impact is higher (ImpactWorld+ 2014). Likewise, geographical distributions of the processes might be also applied when determining the location of each activity (Mutel *et al.* 2012). The uncertainty derived from these spatial distributions might affect not only the inventory results but also the values of the regionalized characterization factors calculated in the software. Therefore, the addition of the process spatial uncertainty to the uncertainty distribution of the dataset exchanges and of the LCIA characterization factors should be considered.

It should also be borne in mind that in the current approach the data from the regional parameters used for calculating the weighted average is only that contained in the intersected area by the process geometry. However, as the full impact from a source can cover areas extending several hundred to thousand kilometers (Potting and Hauschild 2006), using site-specific locations in the inventory might reduce the accuracy of the results. Therefore, it might be necessary to analyze the feasibility of enhancing the current implementation approach to also include transport pathways of emissions when calculating the regionalized characterization factors.

Moreover, the seasonal variation of the regional parameters is currently dismissed as annual averages are commonly used, for example, in the water scarcity ratios calculation. However, this might affect the impact results considerably as some crops are only grown during specific times of the year. Therefore, future advances in the software implementation of regionalized LCIA should also integrate the temporal variable.

Finally, LCIA results obtained from spatially heterogenic systems, i.e. multi-scale systems, should be carefully interpreted: processes using generic characterization factors, which tend to be higher than site-dependent factors (Table 1), might have higher contributions to the overall impact than expected. Therefore, the decision of performing a regionalized LCIA must be along with the goal of the study whilst bearing in mind the added complexity to the analysis of the results derived from this type of assessment.

5. Conclusion

Considering the high variability of LCI and LCIA results between the different locations analyzed, regionalized assessments for finer spatial resolutions than countries should be conducted both in the inventory and impact assessment phases for agricultural systems. To this end, LCIA method developers should provide the regional parameters used for calculating the characterization factors using suitable spatial resolution. Higher transparency in the calculations applied for the different impact categories will also help to implement their methods in openLCA. Likewise, LCA database providers should consider the necessity of modeling the data sets at higher spatial resolutions than national or supranational scales. The currently integrated approach in openLCA allows to perform fully regionalized LCAs without increasing considerably the complexity of the calculations. However, this first step in the implementation must be followed by further enhancements which will allow to minimize the uncertainty and increase the validity of the impact assessment results.

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7. References

Bengtsson M, Carlson R, Molander S, Steen B (1998) An approach for handling geographical information in life cycle assessment using a relational database. J Hazardous Materials 61: 67–75

Bentrup F, Küsters J, Kuhlmann H, Lammel J (2004) Environmental impact assessment of agricultural production systems using the life cycle assessment methodology: I. Theoretical concept of a LCA method tailored to crop production. Eur J Agronomy. doi: 10.1016/S1161-0301(03)00024-8

de Baan L, Alkemade R, Koellner T (2012) Land use impacts on biodiversity in LCA: a global approach. Int J Life Cycle Assess. doi: 10.1007/s11367-012-0412-0

ETH Zürich (2014) Enhanced Ecoindicator99 (EI99+) characterization factors retrieved from http://www.ifu.ethz.ch/ESD/downloads/EI99plus. Accessed 27 February 2014

Frischknecht R, Jungbluth N, Pfister S (2009) UBP-Bewertung für den Wasserbedarf von Treibstoffen. ESU-services, Uster, im Auftrag des Bundesamtes für Umwelt (BAFU), Bern, C.H.

Frischknecht R, Büsser Knöpfel S (2013) Swiss Eco-Factors 2013 according to the Ecological Scarcity Method. Methodological fundamentals and their application in Switzerland. Environ studies no. 1330. Federal Office for the Environment, Bern: 254 pp.

Gerber PJ, Steinfeld H, Henderson B, Mottet A, Opio C, Dijkman J, Falcucci A, Tempio G (2013) Tackling climate change through livestock – A global assessment of emissions and mitigation opportunities. Food and Agriculture Organization of the United Nations (FAO), Rome.

GeoTools (2013) Java GIS toolkit v. 10.3 retrieved from http://www.geotools.org. Accessed 20 December 2013

Geyer R, Stoms DM, Lindner JP, David FW, Wittstock B (2010) Coupling GIS and LCA for biodiversity assessments of land use. Part 1: Inventory modeling. Int J Life Cycle Assess 15:454–467

Gotway CA, Young LJ (2002) Combining Incompatible Spatial Data. J of the Am Statistical Association 97:632-648

Halog A, Bortsie-Aryee NA (2013) The need for integrated life cycle sustainability analysis of biofuel supply chains. Biofuels – Economy, Environment and Sustainabilty. doi: 10.5772/52700

Harris S, Narayanaswamy V (2009) A literature review of life cycle assessment in agriculture. RIRDC Publication No. 09/029 and RIRDC Project No. PRJ-002940, Rural Industries Research and Development Corporation, Barton, Australia.

ImpactWorld+ (2014) http://www.impactworldplus.org/en/presentation.php. Accessed 25 April 2014

Kier G, Mutke J, Dinerstein E, Ricketts TH, Kueper W, Kreft H, Barthlott W (2005) Global patterns of plant diversity and floristic knowledge. J Biogeography, 32:1107–1116

LCA Digital Commons (2013) LCI Database retrieved from https://www.lcacommons.gov/discovery. Accessed 12 December 2013

Liu KFR, Hung MJ, Yeh PC, Kuo JY (2014) GIS-Based Regionalization of LCA. J Geosci. and Environ. Protection, 2, 1-8. doi: 10.4236/gep.2014.22001

Manneh R, Margni M, Deschênes L. (2010) Spatial variability of intake fractions for Canadian emission scenarios: a comparison between three resolution scales. Environ Sci Technol 44(11):4217-24. doi: 10.1021/es902983b

Mutel C (2009) GIS-based regionalization and implementation in new data formats. Discussion Forum on LCA. http://www.lcaforum.ch/portals/0/df39/DF39-07%20Mutel-GIS-based%20regionalization.pdf. Accessed 28 November 2012.

Mutel CL, Pfister S, Hellweg S (2012) GIS-based regionalized life cycle assessment: how big is small enough? Methodology and case study of electricity generation. Environ. Sci. Technol. 46, 1096−1103

Nuñez M, Civit B, Muñoz P, Arena AP, Rieradevall J, Antón A (2010) Assessing potential desertification environmental impact in life cycle assessment. Part 1: Methodological aspects. Int J Life Cycle Assess 15:67–78

Payraudeau S, Van der Werf HMG (2005), Environmental impact assessment for a farming region: a review of methods. Agr. Ecos. & Env., 107, 1-19

Perveen S, James LA (2009) Multiscale effects on spatial variability metrics in global water resources data. Water Resour Manage. doi: 10.1007/s11269-009-9530-2

Pfister S, Koehler A, Hellweg S (2009) Assessing the Environmental Impacts of Freshwater Consumption in LCA. Enviorn Sci Technol 43:4098-4104

Plumejeaud C, Prud'homme J, Davoine P-A, Gensel J (2010) Transferring Indicators into Different Partitions of Geographic Space. Lec. Notes Comput. Sci. Eng. 6016:445−460

Potting J, Hauschild MZ (2006) Spatial Differentiation in Life Cycle Assessment. A decade of method development to increase environmental realism of LCIA. Int J LCA 11. Special Issue 1:11-13

Pradeleix L, Bellon-Maurel V, Roux P, Philippon 0, Bouarfa S (2012) Life Cycle Assessment at the regional scale: innovative insights based on the systems approach used for uncertainty characterization. HAL. http://hal.archives-ouvertes.fr/docs/00/76/51/78/PDF/mo2012-pub00036280.pdf. Accessed 30 April 2014.

QuantumGIS (2012) v.1.8.0-Lisboa downloaded from http://www.qgis.org. Accessed 7 December 2012.

Treeze Ltd (2014) Ecological Scarcity Method 2013 characterization factors and GoogleTM earth layer for water use scarcity retrieved from http://treeze.ch/projects/methodology-development/life-cycle-impact-assessment/ecological-scarcity-method-2013/. Accessed 26 February 2014

US Census Bureau (2014) http://www.census.gov/cgi-bin/geo/shapefiles2013/layers.cgi. Accessed 20 April 2014.